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Posted Date: 24 April 2026

doi: 10.20944/preprints202604.1718.v1

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Model-Aware Predictive Control for Occupant-Centric Environment Optimization in Room-Level Scenarios

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Abstract

The global drive towards sustainability and energy conservation has accelerated the development of intelligent buildings utilizing building management system (BMS). Occupants have profound impacts on building environment. Incorporating occupant-related factors into the environmental control process is essential for optimizing the efficiency of BMS, which thus give rise to the concept of occupant-centric control (OCC). Conventional methods rely on simplified models and fixed schedules that fail to satisfy environment control and occupant requirements, while constructing credible models places strict requirements on the dataset. In this paper, we propose a **M**odel-**A**ware **P**redictive **C**ontrol framework named MAPC, which can construct credible models with limited data and provide room-level control strategies allowing for occupant comfort and energy efficiency. Its technological innovations are twofold. On the one hand, we design a model construction and fine-tuning method combining data-driven subspace projection approach with physical priors, which can construct credible thermal dynamic models with limited data. On the other hand, to balance the potential conflicts between enhancing occupant comfort and saving energy, we present a hierarchical decision-making mechanism, which enables room-level global optimal control considering dynamic occupant comfort requirements and energy usage. Experimental results obtained on a typical duplex apartment dataset demonstrate that MAPC is able to provide room-level control strategies based on dynamic occupant requirements and user preferences, achieving improved occupant comfort and energy efficiency. The ablation experiments also demonstrated the superiority of MAPC in constructing reliable models on limited datasets.

Keywords: occupant-centric control; model predictive control; intelligent buildings

1. Introduction

With the rapid development of urbanization, the substantial energy demand of buildings and infrastructure has made it a focal point in the sustainability debate[1]. Currently, the energy consumption of buildings accounts for 30% of the total global energy consumption, demonstrating the significant potential for achieving energy savings in this domain[2]. As a result, energy conservation has become one of the primary control objectives in buildings[3]. As an important tool for building environment control, building management system (BMS) plays a significant role in controlling building energy savings[4]. Meanwhile, the advancement of technology used in BMS has accelerated occupants' pursuit of healthier and more comfortable building environments[5, 6]. Substantially, occupants have become a crucial role in building management[7], thus giving rise to the concept of occupant-centric control (OCC). In this regard, reconciling occupant comfort with energy efficiency has become a research focus[8-11].

Recently, considerable efforts have been undertaken in the field of OCC. Researchers have explored several approaches to integrate environmental requirements into the building control loop[7, 12-14]. Conventional methods mostly adopt rule-based control (RBC), which operates according to fixed schedules and adjusts control parameters primarily relying on empirical knowledge. Technically, RBC often employs the proportional-integral-derivative (PID) method to regulate indoor temperatures toward the desired setpoints[15-19]. As a classic control method, PID has demonstrated its effectiveness in building environmental systems through long-term practice[17]. Nonetheless, PID control operates primarily on scheduled occupancy profiles, resulting in static control strategies and control lag[15, 18]. Therefore, researchers have increasingly focused on integrating dynamic occupant-related factors into control processes, expecting more proactive and optimized system operation results. This has prompted the exploration of advanced control strategies as a promising pathway forward.

Substantially, the existing advanced control methods can be mainly divided into model-driven and data-driven approaches. On the one hand, as a typical model-driven control method, model predictive control (MPC) has gained significant attention due to its inherent capability to incorporate predictive information over a finite time horizon[13, 20-26]. Existing researches on MPC generally utilize the resistance-capacitance (RC) model to represent the heat transfer and storage processes of a building. However, the RC model is a simplified model and may introduce certain inaccuracies[13]. Unfortunately, researchers found it difficult to establish an accurate explicit model for the building thermal dynamics. On the other hand, data-driven methods such as neural networks and reinforcement learning (RL) have attracted researchers' attention[4, 12, 19, 21, 26-32]. These methods are not constrained by fixed formulaic expressions and can depict implicit relationships hidden behind the data. Despite being expert at dealing with complex nonlinear systems without depending on specific models, data-driven methods still face some challenges in terms of training cost, convergence speed, and dataset requirements[33]. Typically, existing methods struggle to establish thermal dynamic models with limited data, and their credibility and interpretability also pose a challenge[34]. Therefore, the exploration of a building environment management framework which can reliably model the thermal dynamics on a limited dataset is urgently needed. Meanwhile, addressing the potential conflicts in room-level control is also of great significance, as the scope of OCC is gradually shifting from single room towards complex spaces[8].

In this paper, we propose a model-aware predictive control framework, named MAPC. Generally, MAPC overcomes the challenge of modeling building thermal dynamics with limited data. Meanwhile, MAPC also retains the ability to provide room-level control strategies considering dynamic occupant comfort and energy saving requirements. Technically, we first design a model construction and fine-tuning method for indoor thermal dynamic, which integrates data-driven subspace projection method with physical priors. Utilizing a data-driven method, this process is able to identify the abstract system state changes with limited dataset quantity and quality, while using the RC model as physical constraints endows the model with higher reliability and interpretability. Second, to balance the potential conflicts associated with distributed control, a hierarchical decision-making framework is presented. A set of rules is proposed for global decision-making and model optimization, with the aim of achieving global energy efficiency optimization while enhancing occupant comfort in room-level control scenarios. To evaluate our method, we utilized a public dataset named CN-OBEE[35] and conducted simulations using data from multiple rooms of a duplex apartment located in Miyun District, Beijing. In particular, we designed an occupant comfort violation index to reflect the ability of methods to enhance occupant comfort. According to the experimental results, MAPC is able to provide room-level control strategies based on dynamic occupant requirements and user preferences, achieving the effect of improving occupant comfort and energy efficiency. To more comprehensively investigate the proposed approach, we designed ablation experiments to discuss the impact of each step on the performance of the model. We envision MAPC as an important prelude to achieving occupant-driven dynamic environmental control in buildings.

 doi:10.20944/preprints202604.1718.v1

In a nutshell, Our contributions are summarized as follows.

- We propose a model-aware predictive control framework oriented to OCC named MAPC, addressing the challenges of constructing credible thermal dynamic models with limited data, and providing room-level environmental control strategies that meet dynamic requirements.
- To construct credible thermal dynamic models, we propose a novel modeling approach that integrates data-driven subspace projection method with physical priors, which can decouple abstract system states from limited data and utilize physical constraints to fine-tune the baseline model, effectively enhancing its reliability and interpretability.
- We propose a hierarchical framework and global decision-making mechanism to balance the potential conflicts associated with distributed control and facilitate the dynamic adaptation of system objectives and constraints by allowing for occupant comfort and energy saving requirements.
- MAPC is implemented utilizing data from multiple rooms in a typical duplex apartment. It is extensively compared with different methods, and we conduct ablation experiments on it. Experimental results demonstrate the superiority of MAPC method in terms of thermal dynamic modeling, enhancing occupant comfort, and energy conservation.

The subsequent sections are organized as follows. We first review the recent literature in Section 2. The principles and the technical details of MAPC are then explained in Section 3, which is followed by discussions on the experimental results and evaluations in Sections 4 and 5 respectively. Finally, we provide a summary of this paper in Section 6.

2. Literature Review

With respect to buildings, researchers have reached a consensus that occupants have a significant effect on building energy efficiency and environment control. For example, Cuerda et al. reported that the difference in energy consumption between actual occupant data and fixed standard data can reach 15%[36]. Ma et al. deconstructed building energy consumption from three perspectives, i.e. physics, occupants, and white noise, and improved the accuracy achieved when characterizing the impact of occupants on energy consumption by more than 50%[37]. However, how to precisely elucidate the impacts of occupant-related factors and further incorporate them into building environment control is still an important scientific issue for BMS. The research efforts in this regard are as follows.

2.1. Rule-Based Control

Conventional BMS primarily implement RBC[19], which means controlling the building operating parameters such as temperature setpoints according to fixed operating rules and occupancy schedules. Specifically, RBC generally utilizes the PID control method to regulate the target parameters to the desired setpoints[38, 39]. PID control is a classic control method. Owing to its advantages of simple principles, strong robustness, and wide practicality, PID control is widely applied in fields like building lighting[38] and HVAC system[39]. For example, Sultan et al. designed a PID control strategy to process real-time temperature and humidity sensor data, output control signals for the fluid control valve of a coil, and ultimately maintain the temperature of a room at the set point[17]. However, the fixed rules and occupancy schedules make RBC methods unable to respond to dynamic occupant-related factors, resulting in static control strategies and control lag[15, 18]. Meanwhile, as the scope of research shifts towards complex systems in multiple spaces, PID control may face the problems of low global performance and conflicts among multiple objectives[15].

Therefore, how to integrate dynamic occupant-related factors into the building control loop and resolve the competing objectives inherent in distributed control remain a key scientific challenge. Advanced control methods provide solutions to these problems, which primarily fall into two categories: model-driven control and data-driven control.

2.2. Model-Driven Control

Model-driven control methods utilize precise physical models for environmental management, providing the possibility of integrating dynamic occupant data into the building control loop. Among the existing approaches, MPC is a sophisticated method that has the ability to solve the optimal control strategy utilizing predictive information within a finite future time horizon, and this method has been widely applied to BMS[22, 40, 41]. For example, Gupta et al. calculated the estimated time of arrival (ETA) of occupants based on their living locations and the distance from home, and then communicated it to the MPC controller to ensure that the house reached the temperature setpoint when the occupants arrived[42]. Wang et al. designed a hierarchical nonlinear model predictive control (HNLMPC) method that can dynamically optimize the temperature setting strategy by predicting future factors including occupancy levels[26]. Meanwhile, Jiang et al. developed an OBMPC system. By predicting future disturbances including occupant behaviors, OBMPC calculates the optimal control strategy to reduce energy consumption levels while ensuring air quality[13].

However, MPC faces challenges such as the difficulty in obtaining accurate physical models[11]. The effectiveness of MPC operation heavily relies on the accuracy of the system model, while establishing an accurate explicit model for the building environment is difficult. Existing studies mostly adopt the resistance–capacitance (RC) model as the fundamental model, which is a simplified model that lacks accuracy. In addition, MPC has difficulty in accommodating the heterogeneous control demands arising from diverse functional zones within buildings. Therefore, the primary challenge faced by model-driven control methods is how to construct an accurate building thermal dynamic model with limited data sources and meet room-level heterogeneous demands.

2.3. Data-Driven Control

With the support of advanced theory and intelligent algorithms, existing data-driven methods have demonstrated a series of prominent outcomes[19, 21, 32]. These methods are not constrained by the expression of fixed formulas, and break through the limitations of artificially defined finite relations, enabling them to capture the implicit relationships hidden behind the data. For example, Tohid et al. used the numerical algorithms for subspace state space system Identification (N4SID) method to identify the abstract thermal dynamics of the system instead of the commonly used RC model, and the average coefficient of variation of the root mean square error (CVRMSE) of the models was 0.84%[19]. Deng et al. utilized transfer learning to predict the occupancy in buildings and provided optimal control strategies[43]. Meanwhile, Gou et al. designed a MLP-VQGAN surrogate model that maps continuous HVAC control parameters to physical fields and proposes an adaptive ventilation strategy. Furthermore, due to its ability to implement adaptive and online learning in unknown or complex environments, RL is gradually becoming a cutting-edge method in OCC[11]. For instance, Chen et al. implemented RL-based HVAC control in a test room using real-time occupancy information sensed by camera sensors and predefined schedules. Moreover, Arroyo et al. innovatively combined the constraints of MPC with the long-term value-based optimization capabilities of RL, enabling constraint satisfaction and continuous learning while achieving performance similar to that of MPC in deterministic settings[21]. Similarly, Parisa et al. utilized a dynamic model identified by a long short-term memory neural network (LSTM) and designed an upper-level controller based on RL to provide global decision[32].

However, data-driven methods like RL still face challenges. For instance, the requirements for the high quantity and quality of training data present a major obstacle to addressing the problem of data scarcity and may lead to poor model robustness[33]. Furthermore, the black-box nature of RL presents significant challenges for ensuring model credibility and operational safety. Researches have demonstrated that adding certain physical constraints can effectively enhance the performance of data-driven methods on small sample datasets and guide the model to learn fundamental patterns, thereby increasing the credibility and interpretability of the model[34]. Therefore, there is an urgent need for a method of building thermal dynamic modeling that integrates data-driven approaches with physical priors.

2.4. Existing Challenges

In summary, with respect to adopting MAPC in smart buildings, several technical challenges still exist and need to be addressed. ***(1) How to depict the implicit dynamics of the building thermal environment from limited data.*** The conventional model-driven methods adopt simplified models and require knowledge of building envelope and thermal parameters, while the effectiveness of data-driven methods depends on the quantity and quality of the dataset. This makes conventional building environment datasets inadequate to meet the training requirements. ***(2) How to integrate control method driven by limited data with reliable physical priors.*** Although the models utilized in model-driven methods offer reliable physical priors to the training of data-driven methods, the critical challenge of harmonizing these disparate modeling paradigms persists. How to embed these physical priors into the learning framework as effective constraints or objectives remains a key scientific problem. ***(3) How to strike a balance between building energy efficiency and dynamic occupant comfort requirements in room-level control.*** This problem is challenging, as the conventional methods rely on fixed occupant schedules because of the randomness of occupant-related factors, resulting in distorted and lagged control results. Moreover, to achieve better control effects, building environment control requires the potential conflicts between objectives, such as energy efficiency and occupant comfort requirements, to be balanced. However, the conventional MPC technique lacks global optimization capabilities, and its constraints and objectives cannot be updated online, making it unable to adapt to real-world situations.

3. Methodology

3.1. Overview

To address the above issues, we seek to explore a hybrid control framework oriented towards OCC. On the one hand, in terms of model construction, it can integrates data-driven methods with physical priors, achieving the goal of depicting the building thermal dynamics with limited data. On the other hand, in terms of system operation, it also has the ability to strike a balance between conflicting objectives and provide room-level control strategies allowing for dynamic occupants comfort and energy saving requirements.

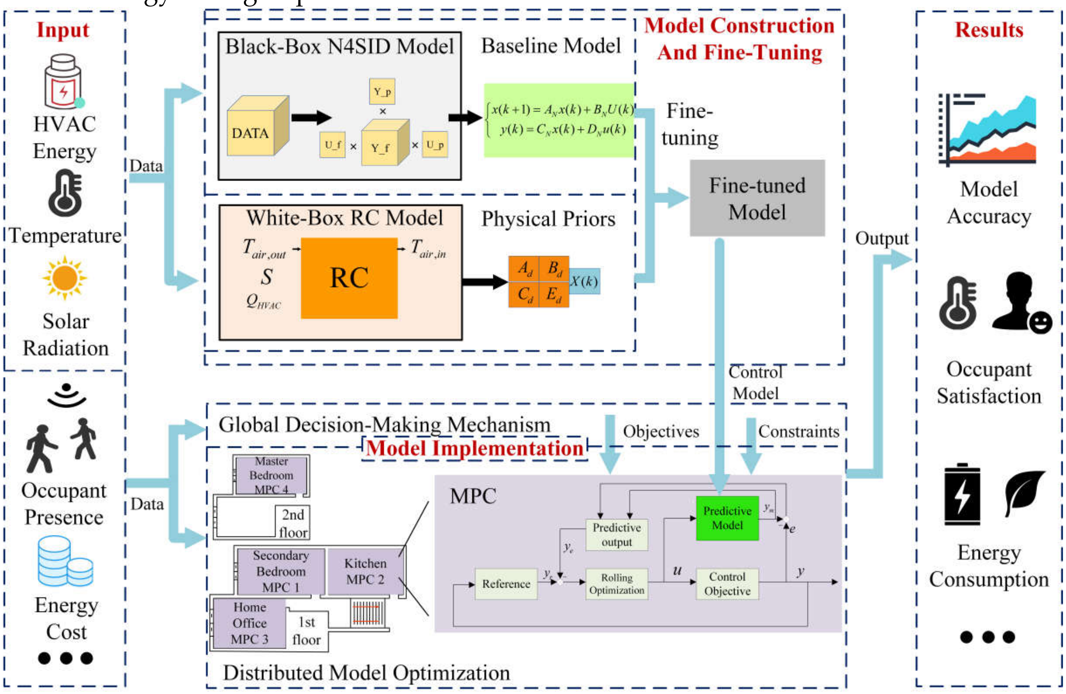

Figure 1. MAPC System Architecture.

Therefore, we establish a model-aware predictive control structure named MAPC, and its basic principles are proposed in this paper. MAPC can be divided into two processes, i.e. **model construction and fine-tuning**, and **model implementation**, as shown in Figure 1. In terms of model construction and fine-tuning, to extract the implicit relationships between occupants and the environment from limited data, MAPC first utilizes the data-driven subspace projection method to identify the initial baseline models of the indoor environment which represent the abstract thermal dynamics of the system. Meanwhile, MAPC constructs RC physical models of each room. Then, MAPC incorporates the states of the RC models as physical priors into the data-driven training process. Starting from the baseline model, MAPC then fine-tunes it to obtain a credible gray-box model. Furthermore, in terms of model implementation, a hierarchical framework and a global decision-making mechanism are proposed to strike a balance between the conflicting objectives brought about by distributed control. This mechanism is able to formulate dynamic occupancy and predicted energy usage as explicit constraints and objective functions, which are then passed to MPC controllers to conduct room-level distributed model optimization.

Then, In the following sections, we will introduce the basic principles of the MAPC, deconstruct its model construction and fine-tuning principles, and explain its hierarchical operation logic.

3.2. Baseline Model Construction

Utilizing a collaborative approach of data-driven methods and physical priors, MAPC is primarily responsible for constructing the credible state space equations for each room, given the limited quantity and quality of the dataset.

In this section, to first obtain the baseline model, we adopted the subspace projection and identification method to learn the State Space (SS) prediction model of the building thermal dynamic from the raw data. Above all, we will introduce the definition of the SS model.

Mathematically, a state space equation can be modeled as follows:

$$\begin{gathered} \frac{dX}{dt} = AX + BU \\ Y = CX + DU \end{gathered} \tag{1}$$

where X denotes the system state variable, U denotes the system input and Y denotes the system output. A, B, C and D represent different system matrices. Despite sharing the same mathematical structure as the RC model, the state X of the SS model does not have direct physical meanings, such as the wall or air temperature. Instead, they represent abstract system states that capture the main thermodynamic dynamics of the building. However, the aforementioned state space model is continuous and requires discretization, i.e.

$$\begin{cases} x(k+1) = A_N x(k) + B_N U(k) \\ y(k) = C_N x(k) + D_N u(k) \end{cases} \tag{2}$$

Specifically, In this paper, the input u includes outdoor temperature $T_{air,out}$, solar radiation S, and air conditioning power Q_{HVAC}, while the output y represents indoor temperature $T_{air,in}$. All of these parameters are extracted from the raw dataset.

Then we will illustrate the principle of the subspace projection and identification method, whose workflow is shown in Figure 2.

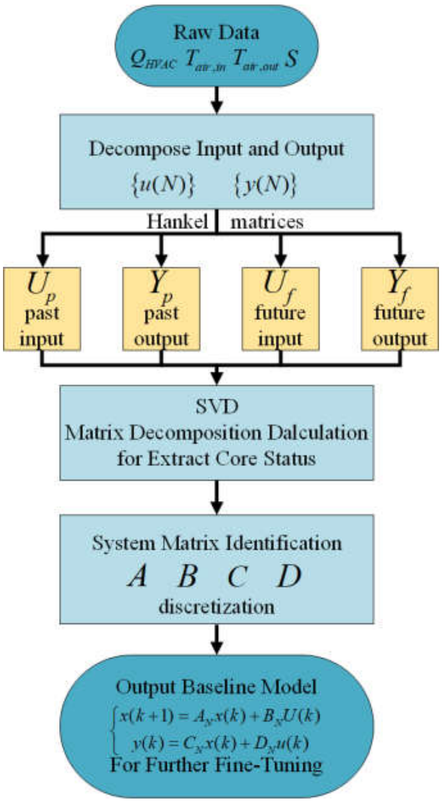

Figure 2. Workflow of the Baseline Model Construction.

First of all, we divide the dataset into input and output, i.e.

$$\{u(1), u(2), ..., u(N)\},\ \{y(1), y(2), ...y(N)\} \tag{3}$$

Then we define two integers i and j, representing the length of the future window and past window respectively. Afterwards, we construct Hankel matrices, i.e.

$$U_p = \begin{bmatrix} u(1) & u(2) & \cdots & u(j) \\ u(2) & u(3) & \cdots & u(j+1) \\ \vdots & \vdots & \ddots & \vdots \\ u(i) & u(i+1) & \cdots & u(i+j-1) \end{bmatrix},\ Y_p = \begin{bmatrix} y(1) & y(2) & \cdots & y(j) \\ y(2) & y(3) & \cdots & y(j+1) \\ \vdots & \vdots & \ddots & \vdots \\ y(i) & y(i+1) & \cdots & y(i+j-1) \end{bmatrix} \tag{4}$$

$$U_f = \begin{bmatrix} u(i+1) & u(i+2) & \cdots & u(i+j) \\ u(i+2) & u(i+3) & \cdots & u(i+j+1) \\ \vdots & \vdots & \ddots & \vdots \\ u(2i) & u(2i+1) & \cdots & u(2i+j-1) \end{bmatrix},\ Y_f = \begin{bmatrix} y(i+1) & y(i+2) & \cdots & y(i+j) \\ y(i+2) & y(i+3) & \cdots & y(i+j+1) \\ \vdots & \vdots & \ddots & \vdots \\ y(2i) & y(2i+1) & \cdots & y(2i+j-1) \end{bmatrix} \tag{5}$$

where U_p and Y_p represent the past input matrix and past output matrix respectively, while U_f and Y_f represent the future input matrix and future output matrix respectively. Furthermore, the past matrix W_p is defined as:

$$W_p = \left[U_p^T, Y_p^T\right]^T \tag{6}$$

By calculating the projection O_n of Y_f on the space spanned by W_p and U_f, we can obtain the system's extended observable matrix Γ_n and state vector X_n, i.e.

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$$O_n = \frac{Y_f}{{}_{u_f}W_p} \approx \Gamma_n X_n \tag{7}$$

After calculating O_n, we further perform singular value decomposition (SVD) on it to obtain the estimated Γ_n and X_n, i.e.

$$O_n = U_1 \Sigma_1 V_1^T \tag{8}$$

$$\hat{\Gamma}_n = U_1 \Sigma_1^{1/2}, \quad \hat{X}_n = \Sigma_1^{1/2} V_1^T \tag{9}$$

Finally, the system matrix A, B, C, D is solved through least squares regression, i.e.

$$\begin{aligned} \begin{bmatrix} \hat{X}_{i+1} \\ Y_i \end{bmatrix} &= \begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{bmatrix} \hat{X}_i \\ U_i \end{bmatrix} \\ \begin{bmatrix} A & B \\ C & D \end{bmatrix} &= \begin{bmatrix} \hat{X}_{i+1} \\ Y_i \end{bmatrix} \begin{bmatrix} \hat{X}_i \\ U_i \end{bmatrix}^T \end{aligned} \tag{10}$$

Therefore, we obtained the baseline model, which was requires further fine-tuning.

3.3. RC-Model-Based Model Fine-Tuning

Meanwhile, to provide reliable physical priors, we established RC models for the building thermal dynamics. RC model is an explicit equation widely recognized and used in academia to describe indoor thermal dynamics, where the state vector includes the external wall temperature $T_{wall,ext}$, the internal wall temperature $T_{wall,in}$ and the indoor air temperature $T_{air,in}$. We consider the air conditioning power Q_{HVAC} as the input U to the system. Furthermore, the outdoor air temperature $T_{air,out}$ and the solar radiation S are considered disturbances D. The system matrices A, B, G contain explicit thermal parameters of buildings. With these notations, the state space model can be established, as shown in Eq. **Error!**.

$$\begin{bmatrix} \dot{T}_{wall,ext} \\ \dot{T}_{wall,in} \\ \dot{T}_{air,in} \end{bmatrix} = A \begin{bmatrix} T_{wall,ext} \\ T_{wall,in} \\ T_{air,in} \end{bmatrix} + BQ_{HVAC} + E \begin{bmatrix} T_{air,out} \\ S \end{bmatrix} \tag{11}$$

Similarly, the aforementioned state space model is continuous and requires discretization, as shown in Eq. **Error!**:

$$\begin{cases} X(k+1) = A_d X(k) + B_d U(k) + E_d D(k) \\ Y(k+1) = C_d X(k) \end{cases} \tag{12}$$

where $A_d = e^{A_c T_s}$, $B_d = (\int_0^{T_s} e^{A_c t} dt) B_c$ and $E_d = (\int_0^{T_s} e^{A_c t} dt) E_c$, and T_s is the sampling time.

We adopt rolling window methods to adaptively update the parameters in the system matrix. By minimizing the difference between temperature prediction results and actual data, we obtain a relatively accurate calibration model.

Finally, we fine-tune the basic model identified by the subspace projection and identification method, using the RC model of the building as a physical constraint, to obtain the final explainable fine-tuned models with physical priors. The loss function for training is set as shown in Eq. **Error!**:

$$J_{loss} = \min \sum_{k=0}^{K} [y(k) - (Cx(k) + Du(k))]^2 + \lambda * \sum_{k=0}^{K} [(Ax(k) + Bu(k) - f_{\_RC}(x(k), u(k)))]^2 \tag{13}$$

where the first term in Eq. **Error!** ensures that the model output closely matches the actual value, aiming for high prediction accuracy. Meanwhile, the second term ensures that the states transition

 doi:10.20944/preprints202604.1718.v1

identified by the data-driven model closely approximate that predicted by the RC model, serving as a physical constraint. The hyperparameter λ is used to balance the importance of the two terms and is determined through hyperparameter optimization.

3.4. Model Implementation

This process is primarily responsible for collecting and preprocessing multisource data, with the aim of balancing the potential conflicts of multi-zone distributed control and providing a global optimization strategy for MPC in each room.

First, we introduce the conventional MPC method. MPC is an advanced control strategy that utilizes a dynamic process model to predict and optimize future system behavior over a finite time horizon, with continuous feedback correction. The three underlying components of MPC include a predictive model, rolling optimization and feedback optimization, which endow it with advantages such as advanced control and online optimization capabilities. The working process and optimization principle of MPC are shown in Figure 3. First, on the basis of the externally set expected output y_{pre} and feedback signal y_c, MPC generates the tracking target y_r for the future time window. Afterward, using the predictive model of the system, the control input u and other inputs are used to predict the system output y_m for the next N steps. The optimal control sequence for the future time domain is solved by minimizing the performance index $\min J(k)$. Finally, only the first optimal control input is executed on the controlled object to produce the actual output y, which is sent to the next moment, thus completing one optimal control step.

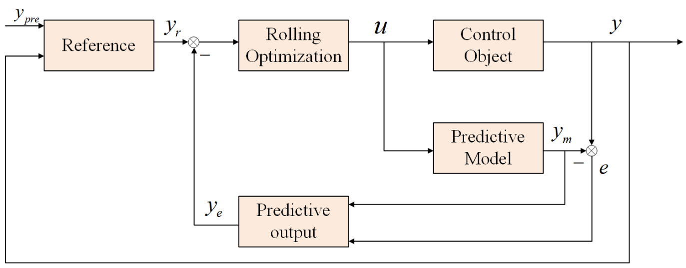

Figure 3. The Working Principle of MPC.

In this paper, the model implementation process can be divided into global decision-making mechanisms and distributed model optimization, as shown in Figure 4. after obtaining the fine-tuned models, MAPC uses them as the predictive models of MPC controllers in each room. Then, the decision-making mechanism provides goals and constraints based on the dynamic requirements of the architectural environment, offering control guidance and suggestions for MPC. Its control approaches are as follows.

Specifically, after obtaining accurate building thermal dynamic models, the global decision-making module is responsible for dynamic planning and energy resource scheduling, with the aim of enabling global optimization and striking a balance between multiple objectives such as conserving energy, ensuring occupant comfort, and prioritizing room allocation.

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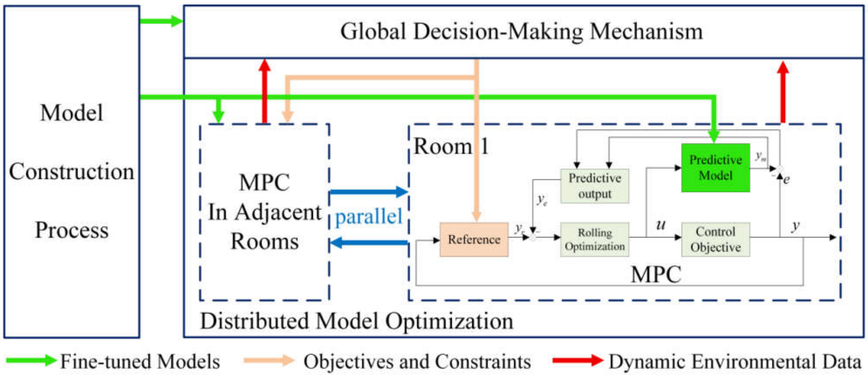

Figure 4. The Working Principle of Distributed Model Optimization.

First, this process acquires the occupant presence of each room in the dataset and calculates the predicted occupancy probability, as shown in Eq. (14):

$$P_h = \frac{\sum_{d=1}^{D} I_{d,h}}{N_h} \tag{14}$$

where $I_{d,h}$ represents the occupant presence status of each room. If the room is occupied in the time interval h on day d, then $I_{d,h}$ is 1. Otherwise, $I_{d,h}$ is set to 0. Then, we design a comfort violation index of the occupants, i.e.

$$C_o = (T_{air,in} - T_{setpoint}) \times (\lambda_o + P_h) \tag{15}$$

$$T_{setpoint} = T_{base} + (T_{max} - T_{base}) * (1 - P_h)^2 \tag{16}$$

where $T_{setpoint}$ is the set temperature of the HVAC system, while T_{max}, T_{base} and λ_o are defined by the user and represent the temperature limit desired by the user and the basic weight of temperature violation respectively. After obtaining the occupant comfort violation index, we can list the objective functions for each MPC, as shown in Eqs. (17):

$$J_{MPC} = \min[\omega_o \sum C_o^2 + \omega_e \sum Q_{HVAC}^2 + \omega_s \sum diff(Q_{HVAC})^2] \tag{17}$$

where C_o represents the occupant comfort term, Q_{HVAC} represents the energy consumption term, and control smoothness term respectively, and ω_o, ω_e, ω_s are the weights of each term, calculated by the following formula:

$$\begin{cases} \omega_o = \omega_{o,base} \times (\lambda_1 + P_h) \\ \omega_e = \omega_{e,base} \times [\lambda_2 + (1 - P_h)] \\ \omega_s = \lambda_3 \end{cases} \tag{18}$$

where λ_1, λ_2 and λ_3 are defined by the users which represents their control preferences. Finally, the MPC controllers in each room operate based on the corresponding models obtained through the model construction process, along with real-time environmental parameters such as occupancy and outdoor temperature, to derive a global control strategy that balances multiple objectives. The entire MAPC process is illustrated in Table 1.

Table 1. Working process of MAPC.

Algorithm 1 Working process
Input: Diverse environmental data $\{T_{air,out}, T_{air,in}, S, Q_{HVAC}, I_{d,h}\}$

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Output: Global air conditioning control strategy that balances objectives such as personnel comfort and energy consumption and simulated control results
1: MAPC uses the N4SID method to identify the base model of each room
2: MAPC establishes RC models for each room
3: Fine-tune the base model utilizing the RC models and input into the MPC controller of each room
4: MPC controllers perform rolling optimization
5: **for** ($t = 0$; $t \le t_{final}$; $t{+}{+}$)
6: The MPC controllers acquire and report dynamic environmental data $\{T_{air,out}, S, P_h\}$
7: The MPC controllers solve **Eq.** (17) and obtain the optimal control sequence $\dot{U}_t$
8: The MPC controllers execute $U_{t,1}$ And calculate the simulation results $T_{air,in,t}$
9: The MPC controllers pass $T_{air,in,t}$ to the next step and continue optimization
10: **end for**
11: The MPC controllers obtain the final control strategy $U(t)$ and simulation results $T_{air,in}$

4. Experimental Study

4.1. Experimental Configuration

4.1.1. Scene and Software Setup

In this section, we verify MAPC on a public room-level building environmental and occupancy dataset, named CN-OBEE. CN-OBEE provides a dataset containing a full year of data. With regard to the location, the dataset was collected in a duplex apartment inhabited by a typical urban family of three in Miyun District, Beijing. The dataset includes information on occupant presence as well as indoor and outdoor environmental data such as temperature, solar radiation, and energy consumption of various appliances. This paper utilizes data from the four typical rooms, including a Master Bedroom, a Secondary Bedroom, a Home Office and a Kitchen. The layout of the rooms is shown in Figure 5. Each room is equipped with an independent split-type air conditioner. Regarding the time series, to simulate the situation of a limited dataset, we used data collected in August 2021. The time interval for indoor data is 1 minute, while that for outdoor data is 1 hour. To align the time scale of the data, we assume that the outdoor data within one hour represents a smooth transition between the actual two consecutive data points. Missing data points are filled with the median of the surrounding data. The final dataset is divided into chronological order, with 70% used for training the model, 10% for validation, and the remaining 20% for testing.

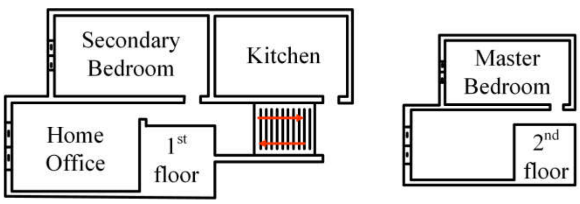

Figure 5. Layouts of the Rooms on Different Floors.

The occupancy probability in each room is calculated every half an hour, as shown in Figure 6, where different colored lines represent the occupancy probability of different rooms. In addition, the input data include outdoor environmental data such as outdoor temperature and solar radiation, as shown in Figure 7. Here, the red curve represents the outdoor temperature, and the yellow curve

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represents the solar radiation level, which are sourced from the national meteorological station in Miyun District. In this paper, we conduct experiments using data from 0:00 to 8:00 on August 25th. In order to simulate the operation results under different user preferences, we design two operating modes for MAPC, i.e. the comfort mode which pays more attention to occupant comfort, and the energy saving mode which focuses more on energy conservation. The parameter settings for the formulas of each mode are shown in Eqs. (19)-(20).

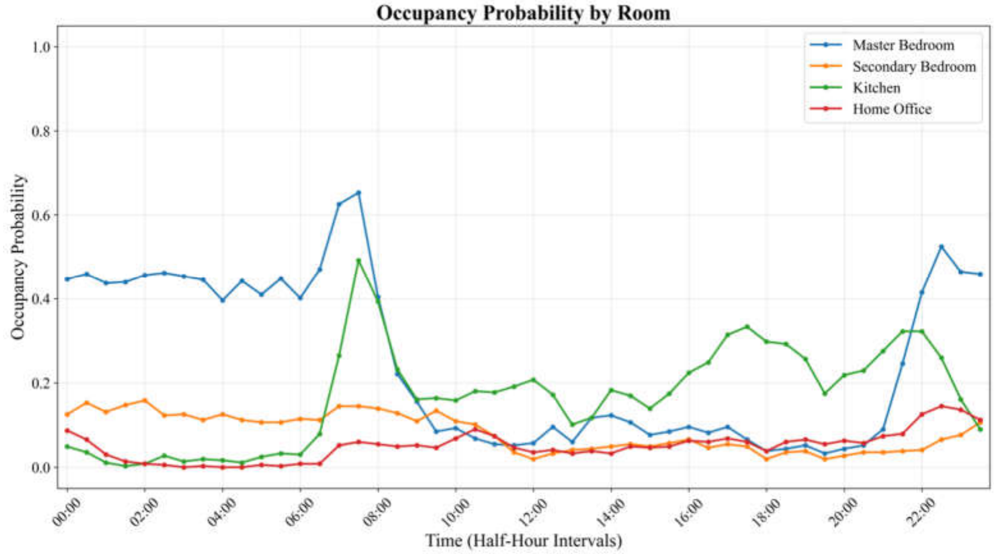


Figure 6. Occupancy Probability in Each Room.

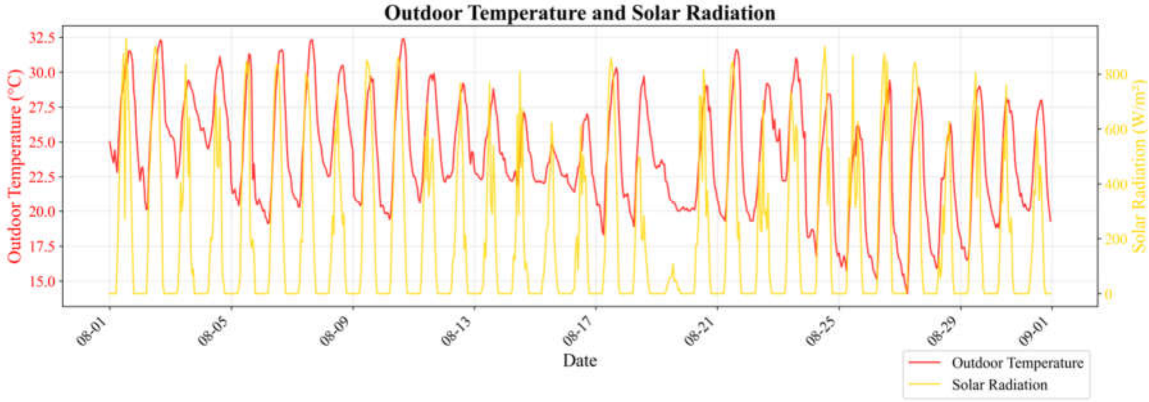


Figure 7. Typical Environmental Conditions in Each Season.

$$T_{max} = 28°C, \quad T_{base} = 24°C, \quad \lambda_0 = 0.2 \tag{19}$$

$$\begin{cases} \lambda_1 = 0.4 \\ \lambda_2 = 0.1 \quad (\text{Comfort Model}) \\ \lambda_3 = 0.01 \end{cases} \qquad \begin{cases} \lambda_1 = 0.2 \\ \lambda_2 = 0.3 \quad (\text{Energy Saving Model}) \\ \lambda_3 = 0.01 \end{cases} \tag{20}$$

4.2. Performance Evaluation

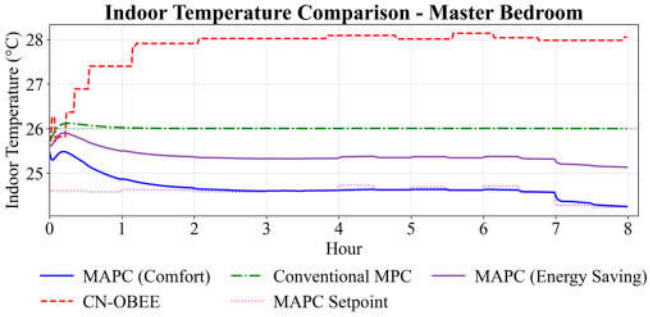
4.2.1. Evaluation Metrics

We first choose appropriate metrics to evaluate the performance of MAPC. (1) Indoor temperature control results are used to reflect the direct impact of the control scheme on the indoor environment. These results demonstrate the precise regulation capability of this method towards the environment and whether it can meet the control requirements of the user. (2) Energy consumption is used to reflect the impact of control schemes on building energy efficiency. The lower the energy consumption, the higher the energy-saving level of the method. (3) The occupant comfort violation index, which refers to the degree to which the indoor environment violates the occupants' needs, taking the occupancy probability into account. The lower the occupant comfort violation index, the more the current environment is able to meet the occupants' needs.

4.2.2. Overall Performance

Taking all the parameters and indicators into consideration, the energy-saving ability of the proposed method and its ability to meet dynamic occupant needs are important concerns. We first define the control strategies and results provided in the dataset as a baseline. Then, we simultaneously compare the results of temperature control, occupant comfort violation index, and energy consumption under each mode of MAPC with those obtained under baseline control and conventional centralized MPC, as shown in Figure 8. The red dashed line in the figure represents the baseline temperature control results from the dataset and the green curve represents the temperature control results of conventional MPC, while the purple and blue curves represent the control results of the two modes of MAPC, respectively.

It is obvious that MAPC can provide room-level control strategies based on dynamic occupant requirements and control modes. Specifically, the comfort mode of MAPC demonstrates superior performance in maintaining indoor temperatures closer to the desired setpoints, while the energy saving mode prioritizes energy conservation at the expense of looser temperature regulation. Moreover, compared with baseline control, the indoor temperature of each room under both two MAPC control modes can align with user-defined control dynamic objectives, providing optimal control objectives that balance occupant comfort and energy conservation goals. Meanwhile, compared with conventional centralized MPC, MAPC can dynamically adjust personalized control strategies for each room. In rooms with high environmental requirements such as occupant comfort, MAPC can adjust control objectives to better meet occupant comfort needs, while allowing MPC controllers to focus more on temperature tracking. While in the opposite situation, MAPC releases the pressure on temperature control, adopts optimization logic that focuses more on energy conservation, and reduces cooling energy consumption.



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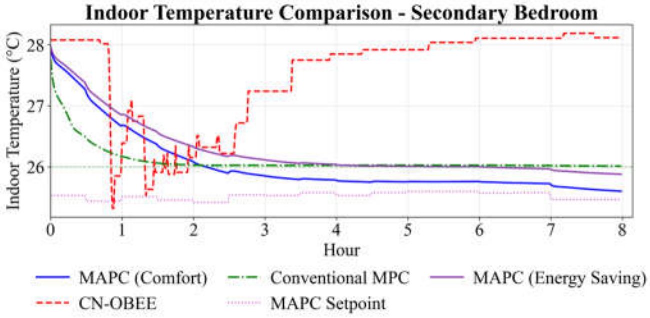

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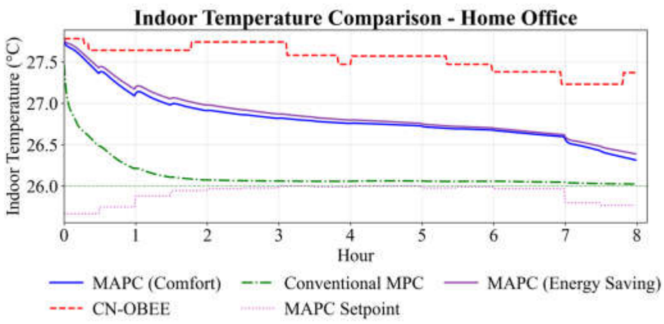

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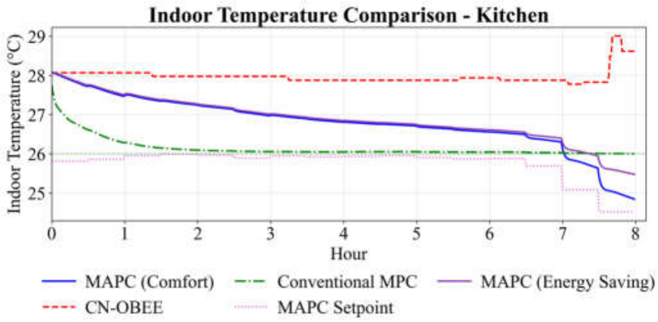
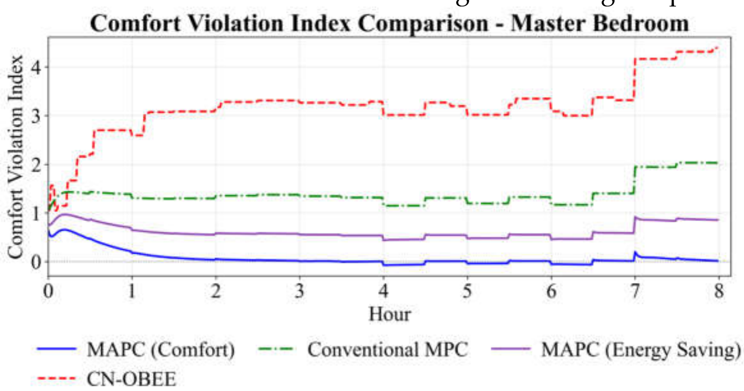


(**d**)

Figure 8. Indoor Temperature Control Results Comparison in Each Room. (a) Indoor Temperature in Master Bedroom. (b) Indoor Temperature in Secondary Bedroom. (c) Indoor Temperature in Home Office. (d) Indoor Temperature in Kitchen.

In addition, we also compared the comfort violation index of each room under different strategies, as shown in Figure 9. Clearly, mainly considering the occupancy probability, the comfort mode of MAPC can maintain the lowest value in most cases, reflecting its excellent ability to meet occupant comfort requirements. The index in energy saving mode has increased, but it can still maintain a level lower than the conventional MPC during times of high requirements.



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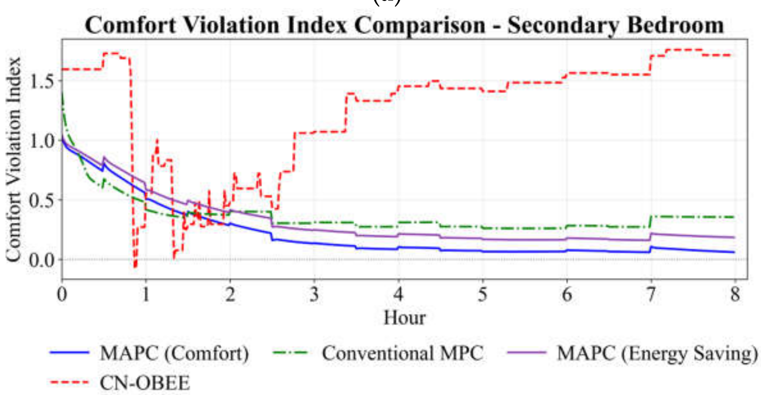

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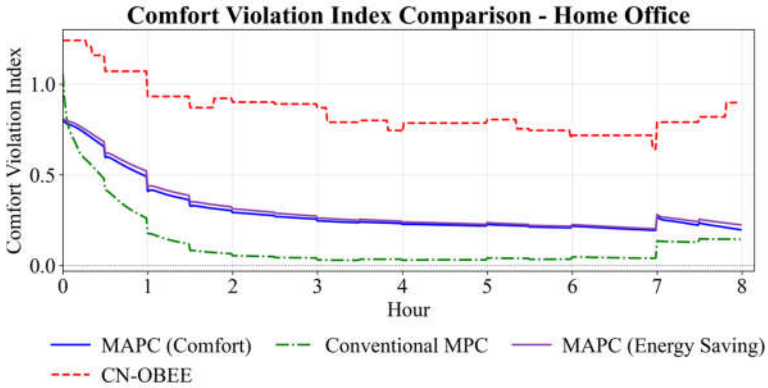

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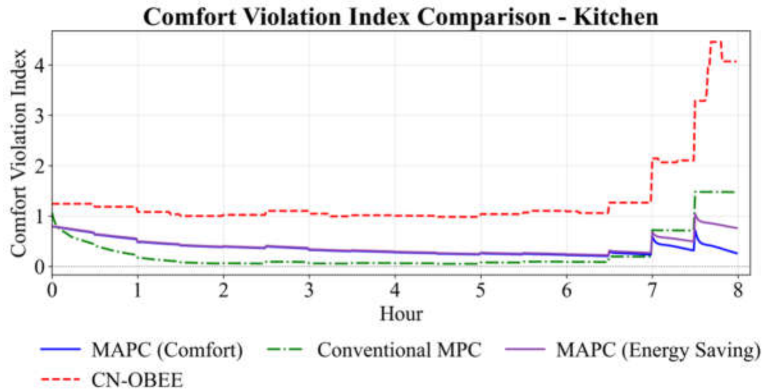
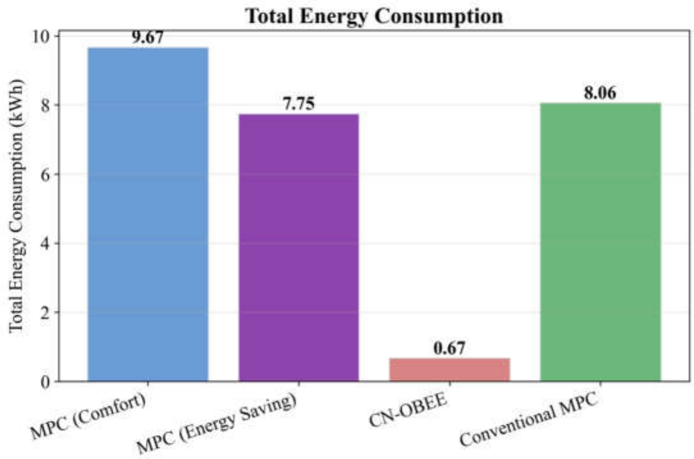


(**d**)

Figure 9. Occupant Comfort Violation Index Comparison Results. (a) Comfort Violation Index in Master Bedroom. (b) Comfort Violation Index in Secondary Bedroom. (c) Comfort Violation Index in Home Office. (d) Comfort Violation Index in Kitchen.

Furthermore, in terms of energy conservation, MAPC can balance the goals of energy conservation and meeting dynamic environmental requirements under relatively limited energy resources, using the least amount of energy to enhance occupant comfort, as shown in Figure 10. Specifically, compared with the conventional centralized MPC, the control strategy provided by the comfort mode of MAPC can reduce the occupant comfort violation index by 55.4% while only increasing energy consumption by 14.7%. Meanwhile, the energy saving mode of MAPC achieves a 44.3% reduction in the comfort violation index along with a 7.7% decrease in energy consumption.



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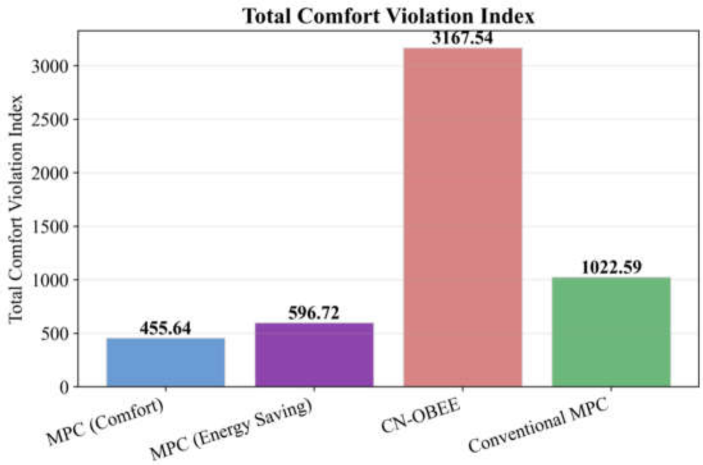


(**b**)

Figure 10. Total Energy Consumption and Comfort Violation Index Comparison. (a) Total Energy Consumption Comparison. (b) Total Comfort Violation Index Comparison.

Last but not least, to evaluate its ability to handle highly dynamic occupant-related information, We compared the average running time of MAPC in one time step with that of conventional centralized MPC, as illustrated in Figure 11. Obviously, MAPC demonstrated significantly faster performance, with an average optimization time of 324.75ms versus 1017.86ms for conventional MPC, representing a 68.1% decrease. This result clearly demonstrates that the distributed architecture of MAPC, which operating on low-dimensional state spaces, directly translates to significant runtime savings compared to the high-dimensional optimization in conventional centralized MPC. The reduced computational latency enables MAPC to process real-time, highly dynamic occupant data rapidly and effectively, facilitating near real-time adaptation and avoiding control delays.

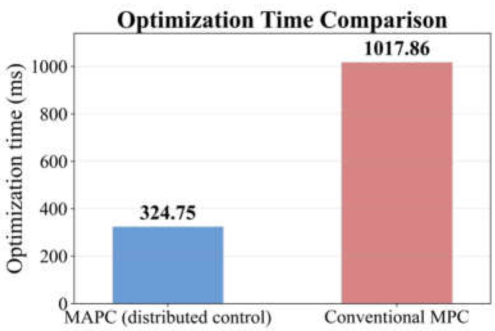


Figure 11. Operation Time Comparison between MAPC and Conventional MPC.

4.2.3. Ablation Experiments

In this section, to demonstrate the accuracy and effectiveness of the data-driven model with physical priors used by MAPC, we designed two sets of ablation experiments, removing the N4SID data-driven part and the RC model-driven parts, and comparing the predictive ability of the MAPC model with the purely model-driven model and the purely data-driven model, as shown in Figures 12-13. The green curve represents the MAPC model, the blue curve represents the model that dissolved the data-driven part, the red curve represents the model that dissolved the model-driven part, and the black curve represents the actual value. Evidently, compared to the two ablated models, the data-driven model Integrating physical priors used by MAPC can better fit the real indoor temperature data, with an error distribution closer to 0. The specific evaluation metrics of the three models are shown in Table 2-3.

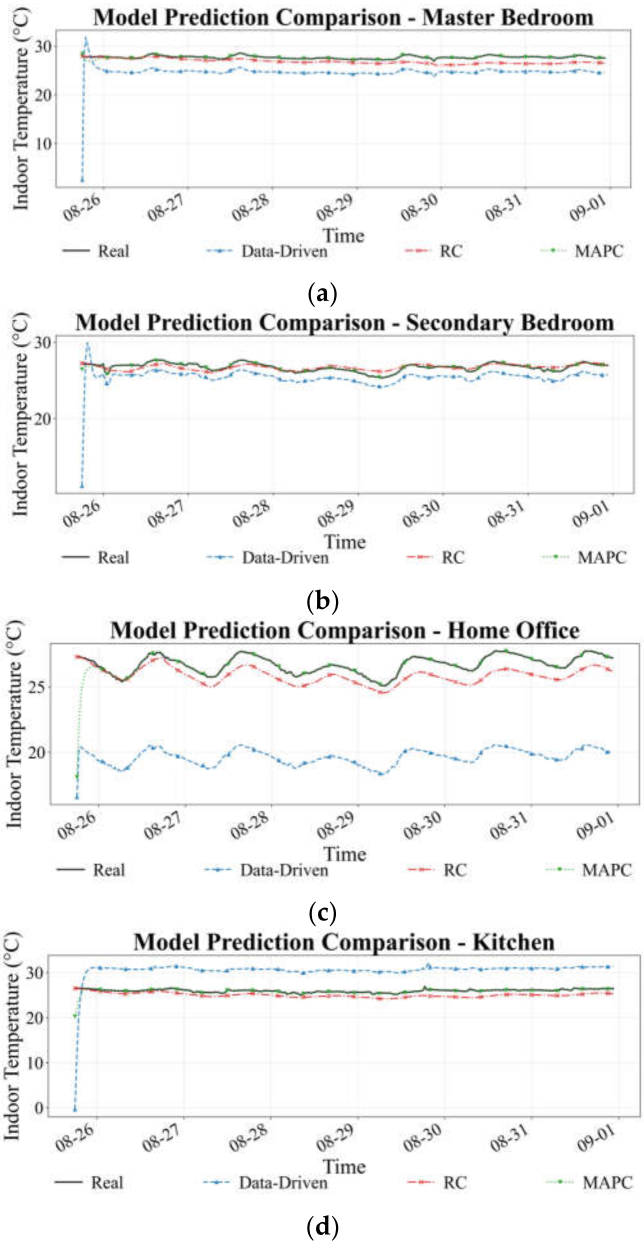
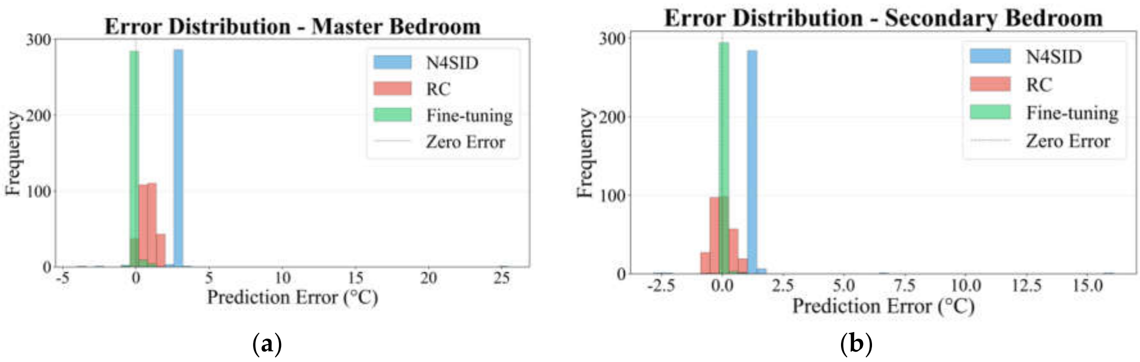
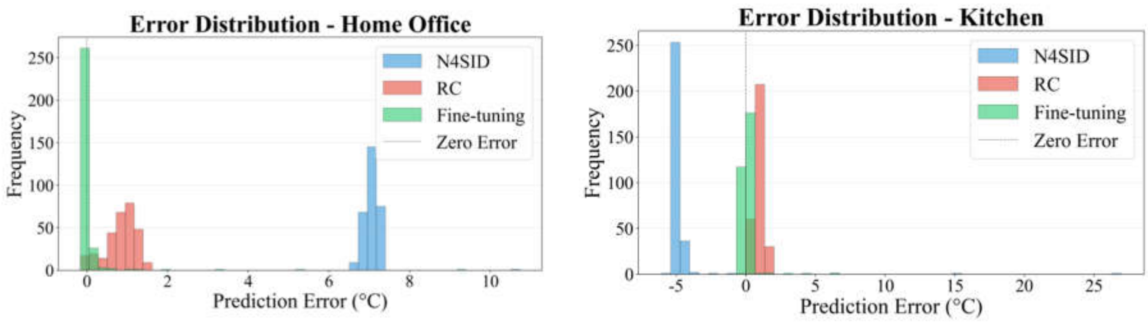


Figure 12. Model Prediction Results Comparison in Each Room. (a) Model Prediction Comparison in Master Bedroom. (b) Model Prediction Comparison in Secondary Bedroom. (c) Model Prediction Comparison in Home Office. (d) Model Prediction Comparison in Kitchen.





(c) (d)

Figure 13. Model Error Distribution Comparison in Each Room. (a) Model Error Distribution in Master Bedroom. (b) Model Error Distribution in Secondary Bedroom. (c) Model Error Distribution in Home Office. (d) Model Error Distribution in Kitchen.

Table 2. Model performance parameters: RMSE and MAE.

Model	Master Bedroom		Secondary Bedroom		Home Office		Kitchen	
	RMSE (℃)	MAE (℃)	RMSE (℃)	MAE (℃)	RMSE (℃)	MAE (℃)	RMSE (℃)	MAE (℃)
Data-driven	3.2817	2.9997	1.6196	1.3349	7.0697	7.0649	5.1172	4.9061
Model-driven	0.9603	0.8453	0.3976	0.3248	0.9230	0.8459	0.9937	0.9369
MAPC	0.1414	0.0447	0.0660	0.0159	0.6640	0.1105	0.4896	0.1093

Table 3. Model performance parameters: MAPE and R^2.

Model	Master Bedroom		Secondary Bedroom		Home Office		Kitchen	
	MAPE (%)	R^2 (/)	MAPE (%)	R^2 (/)	MAPE (%)	R^2 (/)	MAPE (%)	R^2 (/)
Data-driven	10.8286	-134.80	4.9897	-8.76	26.4675	-112.38	18.8946	-247.88
Model-driven	3.0487	-10.63	0.3976	1.2196	3.1553	-0.93	3.6096	-8.38
MAPC	0.1610	0.75	0.0589	0.98	0.4078	-0.01	0.4163	-1.28

Clearly, the fine-tuned model used by MAPC exhibits significant advantages in various performance aspects. Meanwhile, it can also be observed that the purely data-driven approach can capture minor changes in system states, but it cannot fit the actual data well. On the other hand, the purely physics-driven model can generally fit the actual data, but it performs poorly in capturing minor system dynamics. The model used by MAPC combines the advantages of both, enabling the accurate and reliable prediction of environmental changes, while providing higher physical interpretability.

5. Discussion

MAPC demonstrates significant potential for balancing energy conservation and meeting the dynamic occupant requirements like thermal comfort. However, this research still has several problems and limitations that could be solved in future studies.

Firstly, this paper employs a fine-tuned model for open-loop simulation, which has been proven capable of maintaining precise control for 8 hours. However, after running for a relatively longer period of time, the controllability of the system gradually decreases. Therefore, conducting simulations in real scenarios or utilizing platforms such as Energyplus for closed-loop simulations is

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necessary, but seeking higher quality and larger datasets, including building envelope and thermal parameters, to meet the simulation requirements still faces difficulties.

Secondly, in terms of model selection, although this paper adopts a data-driven approach combined with physical constraints, the model trained based on the data-driven subspace projection method still shares the mathematical structure of the state space equation with the RC model, which means that the model still cannot capture the nonlinear relationships in the building environment effectively, resulting in poor model performance. Using machine learning methods such as neural networks to learn the model is a good solution, but this approach still faces issues such as high requirements for datasets and poor interpretability. In recent years, gray-box algorithms such as physics-informed neural networks (PINN), which combine white-box algorithms with black-box algorithms, have also provided new ideas for solving these problems. Gray-box methods enable the control process to follow physical laws in cases with limited datasets, making them more suitable for this field.

Finally, in terms of occupants, owing to the randomness of their behaviors, this paper mainly hopes to address the bridge between the perceptions of occupants and OCC. Therefore, in this paper, the average occupant presence probability within one year is chosen as the input. However, real-time occupants are more diverse and variable. How to more accurately describe and predict occupant changes remains to be further studied. In addition, the passive impacts of occupants on buildings are considered in this study, but the subjective impacts of occupants on buildings have not been fully explored, such as the feedback of occupants regarding the environment and their active energy-related behaviors. It is necessary to consider the impact of such factors on building operation and control.

6. Conclusions

In this paper, we propose a model-aware predictive control framework named MAPC to enhance occupant comfort and limit energy consumption within buildings. Our technical contributions can be summarized as follows. First, we proposed a model construction and fine-tuning and fine-tuning structure combining data-driven methods with physical priors. Based on the subspace projection method and fine-tuned by utilizing RC models, MAPC can identify credible state space models for each room with limited data, which can be used for MPC as predictive models.

Second, to balance the potential conflicts associated with multi-zone distributed control, we propose a hierarchical framework and a global decision-making mechanism based on dynamic rules to ensure that the system can achieve a balance between conflicting objectives and enable room-level optimal control considering both occupant comfort requirements and energy consumption.

Third, we conducted experiments on MAPC in different rooms and under various environmental conditions of a typical duplex apartment, and compared them with conventional methods and baseline control. The results showed that MAPC can effectively balance energy conservation and meet the dynamic needs of occupants while implementing differentiated control schemes for different rooms. Compared with conventional methods, MAPC is able to provide room-level control strategies based on dynamic occupant requirements and user preferences, achieving the effect of improving occupant comfort and energy efficiency. The ablation experiments also demonstrated the superiority of MAPC in constructing reliable models on limited datasets. However, this method has deficiencies in occupant behavior simulation and precise building modeling scenarios. To further overcome these issues, in the future, we will attempt to more accurately model occupant behaviors, and we also expect to integrate data-driven methods such as machine learning and RL to achieve more precise and efficient occupant-driven control for building environments.

Author Contributions: Conceptualization, S.L., Q.Y. and Q.Z.; methodology, S.L.; software, S.L.; validation, S.L and Q.Z.; formal analysis, R.W., H.J., X.Z., Z.D. and Y.W.; investigation, S.L.; resources, S.L.; data curation, S.L.; writing—original draft preparation, S.L.; writing—review and editing, Q.Y. and Q.Z.; visualization, S.L.;

 doi:10.20944/preprints202604.1718.v1

supervision, Q.Y. and Q.Z.; funding acquisition, Q.Y. and Q.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the State Key Laboratory of Disaster Prevention & Mitigation of Explosion & Impact under grant KYFYGKQT0026008, the National Key Research and Development Program of China under grant 2023YFC3107100 and the National Science Foundation of Jiangsu Province under grant no. BK20210439 (corresponding author: Qizhen Zhou).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable..

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

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